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Detection of Renal carcinoma in Ultrasound Images using HOG and SURF features

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Abstract*: *Cancer can be defined as the abnormal growth of cells in any region of the human. Cancer cells possess a special property called metastasis that involves the movement of cells from one location to another location. Renal cancer is becoming predominant and there are different types. One among them is Renal cell carcinoma mainly occurs in the renal tubules. In this study, ultrasound images are considered for the detection of renal cell carcinoma. The images undergo pre-processing to remove speckle noises. The region of interest is defined using region growing technique. Later Feature descriptors like histogram of oriented gradient features and speeded up robust features are extracted from the segmented region for the analysis of carcinoma. Texture features are also derived along with these descriptors. These features are classified using Adaptive Support Vector Machine for the diagnosis of the renal cell carcinoma from normal images. With the performance of the classifier, it is defined that feature descriptors illustrate the region of carcinoma more effectively.

Keywords: Renal cell carcinoma, Gaussian filter, Feature Descriptors, Texture, Adaptive SVM,

I. INTRODUCTION

Kidney is a pair of organs in the abdominal cavity that excrete urine and the inner region is medulla and it contains 8-12 renal pyramids, the pyramids empty into the calyx. Renal artery branches off of the aorta bringing waste filled blood into the kidney for filtering in the nephrons. Nephron is the structural and functional unit of the kidney. Each human adult kidney contains around 1million nephrons. Renal artery is subdivided into several branches inside the kidney. Renal cells that play several essential regulatory roles and their main function is to regulate the balance of electrolytes in the blood Epithelial cells, Endothelial cells and fibroblasts are the main cell types of renal cells.

Renal cell carcinoma is a kidney cancer that originates in the lining of the proximal convoluted tubule and it response to transport primary urine. Renal cell carcinoma (RCC) is the most common type of kidney cancer in adults responsible for approximately 90-95% of cases. In RCC cancer cells start growing uncontrollably in the lining of the tubules of the kidney and it is fast growing cancer and often spreads to lungs and surrounding organs.

The causes of RCC is commonly found in men between the ages 50-70.The main cause is dialysis treatment, hypertension, obesity, Smoking cigarettes, polycystic kidney disease, chronic abuse of certain prescribed and over counter medications such as non-steroidal anti-inflammatory drugs used to treat arthritis. The signs and symptoms are blood in urine, weight loss, a lump in the abdomen, fatigue, vision problems and excessive hair growth in human.

Survey paper of renal cell carcinoma is arising in adults less than or equal to 46 years and it is identified 98/598(16.4%) early onset of RCCs. Median age in the early onset RCC and control group was 38.4 and 62.8 years. The early onset RCC group contained 33/96(34.3%) in females and 63/96(65.6%) in males. Early onset RCCs included 52% clear cell, 28.6% papillary, 8.2% unclassified.

In this paper, renal ultrasound images are derived from the database called Ultrasound cases for the detection and diagnosis of renal carcinoma. Normal and abnormal images are analysed using the defined algorithm. The algorithm involves pre-processing using Gaussian Low pass filter to reduce speckle noise. The renal region of interest is segmented from the images through simple segmentation technique, region growing by defining seed point or pixel for the growth. From the segmented images, HOG, SURF and texture features are extracted to illustrate the presence of carcinoma in the renal regions. Further classification of the two categories is performed with the help of adaptive support vector machine. With these results the carcinoma condition is detected and diagnosed from the ultrasound images.

II. LITERATURE REVIEW

G. R. Jayashree et al. describes and investigates on the development of cancer identification which is expected to improve the performance over previously proposed approaches. The renal cell images that are acquired are noisy. As a result first, the acquired renal cell images are segmented to remove background noise using ROI extraction. CLACHE algorithm is applied to enhance the image. The acquired renal cell images are subjected to binarization. After that GLCM features are extracted.

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Twenty one GLCM features are computed. Among the twenty one features, two best features are selected. The selected features are combined into pairs and given as an input to SVM (Support vector machine), which is used to classify into different grading levels. Finally based on the features, the grading of the patient such as grade1, grade2, grade3, and grade4 are performed. Identification of the cancer is done on the basis of grading levels. Also, the overall accuracy, sensitivity, and specificity of the system were achieved

Birgitte Nielsen et al. illustrate new adaptive features that outperformed the predefined features when applied to the 45 most challenging Brodatz texture pairs. Class distance and difference matrices clearly illustrated the difference in chromatin texture between cell nucleus images from two different prognostic classes of early ovarian cancer. For each of the texture analysis methods, one adaptive feature was found to contain the most discriminatory power.

In the previous work, ultrasound renal images are analysed for the presence of cancer using GLCM features and different texture features. In this study, histogram based oriented gradient and Speeded up robust features are additionally defined for the ultrasound renal images along with the texture features for the classification and detection of renal carcinoma.

III. METHODOLOGY

In this research, renal ultrasound images are derived from the database for the diagnosis of renal carcinoma. The defined algorithm involves pre-processing using Gaussian Low pass filter to reduce speckle noise. The renal region of interest is segmented from the images through simple segmentation technique, region growing by defining seed point or pixel for the growth. From the segmented images, HOG, SURF and texture features are extracted to illustrate the presence of carcinoma in the renal regions. Further classification of the two categories is performed with the help of adaptive support vector machine. With these results the carcinoma condition is detected and diagnosed from the ultrasound images.

Ultrasound cases are special database or library of ultrasound images of more than 7000 images of different disease conditions and criteria's offered by SonoSkills and Hitachi Medical Systems Europe. Images for this research are derived from ultrasound images.

A. Pre-Processing

- ***Gaussian Low Pass Filter***: Speckle noise mainly reduces the levels of contrast with changes in the pixels. Non-linear filtering technique is used to minimise the speckle noise to conserve the contrast levels in an image. Gaussian filter is used to reduce the speckle noise renal ultrasound images [7, 8]. This low pass filter uses different window or kernel that involves bell shaped distribution is defined in the equation (1)

In this method, the images are filtered to reduce the noise and to improve the image quality. Filters smoothens the pixel information with defining fine details. After pre-processing segmentation of the renal region is performed that analyses the state of carcinoma in the renal ultrasound images.

B. Segmentation

In this paper, median filter reduces the speckle noise and the region of interest from the renal carcinoma images are segmented for further analysis and diagnosis using a simple segmentation technique. Region growing technique is used for segregation of the renal regions from the images.

- ***Region Growing***: Region growing approach is the basic technique in segmentation process where the seed point is defined for the growing to describe the region of interest. Region growing can be illustrated as the state opposite of the split and merge technique.
  - An initial set of small areas are iteratively merged according to similarity constraints.
  - Start by choosing an arbitrary seed pixel and compare it with neighboring pixels.
  - Region is grown from the seed pixel by adding in neighboring pixels that are similar, increasing the size of the region.
  - When the growth of one region stops we simply choose another seed pixel which does not yet belong to any region and start again.
  - This whole process is continued until all pixels belong to some region.
  - A bottom up method.

Region growing methods often give very good segmentations that correspond well to the observed edges. In this study the renal images are fixed with a seed pixel which helps in defining the region of interest. From the segmented region, features are extracted for the analysis of the state of carcinoma.

C. Feature Extraction

- ***HISTOGRAM OF ORIENTED GRADIENT FEATURES:***

Histogram of oriented gradient (HOG) is a type of feature descriptor which defines the entire image with few pixel points of representation. HOG focuses on the shape of the region of interest that clearly describes the edges of images with gradient and orientation. Localized portions or regions are formed by breaking the complete image into pieces [9, 10]. These descriptors later form histogram for the gradient and orientation of the pixels. The gradient and orientation is defined in the equation (2) & (3).

$$Gradient\ Magnitude = \sqrt{{G_x}^2 + {G_y}^2} \tag{2}$$

$$\emptyset = \tan^{-1}\frac{G_x}{G_y} \tag{3}$$

G_x and G_y are the vertical and horizontal pixel values in the images. The HOG features are extracted from the segmented renal region to define state of carcinoma whether it is present or not.

- ***SURF FEATURES:*** Speeded up robust features are also a type of feature descriptors used in computer vision for object identification and detection. The algorithm functions in such a way that it defines the key points in the corners, edges and blobs of the objects to illustrate the similarity. Along with these orientation of regions is also described for the complete identification of the region of interest. These features possess multiple scale variants.

SURF features are approximated mask of second order derivative of Gaussian for an image with variant scales. This technique uses mask along and at 45 degrees to the axis making it more robust when compared with other techniques. The process is too fast with the use of the integral image. These images consists of pixel values at (p, q) which is the summation of values in the rectangle described with the origin and pixel values. Images with any size can be computed easily. In this research, SURF features are defined for the renal cells segmented from the images [11].

- ***TEXTURE FEATURES:*** Gray level Co-occurrence matrix (GLCM) defines the features of second order statistical probability X (i, j) that involves features like Correlation, Contrast, Homogeneity and Energy [12, 13]. These features are described below with the equations (4), (5), (6) & (7) in which the gray levels are i and j.

Contrast is defined as the measurement of local intensity or contrast variations between the gray levels.

$$\text{Contrast} = \sum_{n=0}^{G-1} n^2 \{G \sum_{i=1}^{G} \sum_{j=1}^{G} X(i,j)\}, |i-j| \quad (4)$$

Correlation is the measurement of pixel's linear dependency with specified position relative to each other

$$\text{Correlation} = \sum_{i=1}^{G} \sum_{j=1}^{G} (\{i \times j\} X(i,j) - \{\mu x \times \mu y\}) / \sigma x \times \sigma y \quad (5)$$

Homogeneity is the distribution among the gray level pixels of the image.

$$\text{Homogeneity} = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \left({}^{1}/_{1 + (i-j)^2} \right) [P(i,j)] \quad (6)$$

Maximum energy of texture is defined by the gray level distribution of the periodic uniform values.

$$\text{Energy} = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} (X(i,j))^2 \quad (7)$$

HOG and texture features are extracted from the segmented renal carcinoma images for further classification process. With these features, the images are categorized and the nature of carcinoma is analyzed. After the feature extraction, classification process is performed with the help of adaptive support vector machine.

D. CLASSIFICATION

Support vector machines (SVM) is described as supervised machine learning algorithms. This type of machine learning is the points of representation that forms separate divisions through mapping. This process of learning defines a boundary line called decision boundary to define the difference between the classes. In this training process, hyper planes are formed in the D-dimensional spaces which separate the positive and negative samples. Adaptive SVM helps in defining the appropriate decision boundary by adjusting to the sample classes and these differentiate the classes more absolutely [14].

In this method, features are trained using adaptive SVM system for the process of differentiation of normal and carcinoma renal structures. After training, test images are subjected for analysis. Efficiency of the Adaptive SVM classifier is determined using 5-fold cross validation [15]. The accuracy and false rate of the classifier using the performance parameters are compared with these cross validation process. With the classifier results, the ultrasound renal carcinoma images are differentiated and analysed.

IV. RESULTS AND DISCUSSION

In this method, ultrasound images are derived from the database library called Ultrasound cases for the detection of renal carcinoma. More than 100 images are determined for the process of classification and analysis. The original ultrasound renal database image is shown in the Fig. 1.

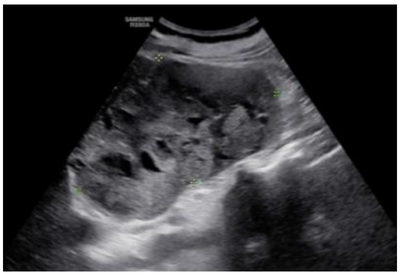

Fig. 1. Original Database image

A. PRE-PROCESSING

In this pre-processing, Gaussian Low pass filter is used to remove speckle noise from the ultrasound renal carcinoma images. The images are filtered and subjected to the process of segmentation. The images of pre-processing are illustrated below in Fig. 2.

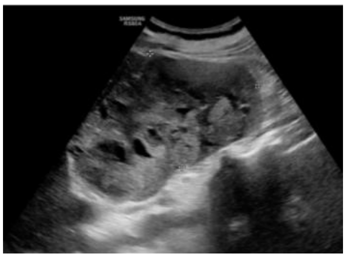

Fig. 2. Pre-processed Renal image

B. SEGMENTATION

After pre-processing, segmentation of the renal regions is performed using a simple technique called region growing. This technique involves the process of fixing a seed pixel point to segregate the renal regions. Features are extracted from these regions for the detection and analysis of presence of renal carcinoma in the images. The segmented image after the process of segmentation technique is shown in Fig. 3.

Fig. 3. Segmented Renal image

After determining the region of interest, the entire region is segregated by superimposing the pixel values with the pre-processed image. The region of interest segregated from the ultrasound image is shown in the Fig. 4.

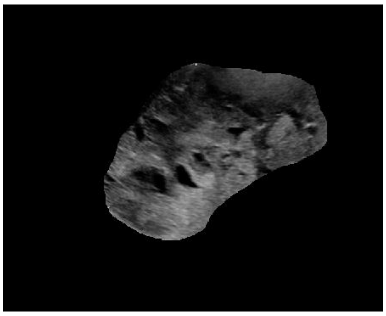

Fig. 4. Superimposed segmented Renal image

C. FEATURE EXTRACTION

After segmentation of the region of interest, feature descriptors like Histogram based oriented gradient (HOG) and Speeded up robust features (SURF) are extracted. Along with these descriptors texture features related to GLCM are derived for the process of differentiation and analysis. (See Table I, II and III).

Table I- Mean values of the features

Subject Categories	Mean values of the features derived					
	HOG	SURF	Contrast	Homogeneity	Correlation	Energy
Normal Subjects	0.3788	0.0549	0.0282	0.9879	0.9769	0.7211
Renal cell carcinoma	0.2777	0.0493	0.0251	0.9896	0.9522	0.8192

Table II- Standard Deviation values of the features

Subject Categories	Standard Deviation values of the features derived					
	HOG	SURF	Contrast	Homogeneity	Correlation	Energy
Normal Subjects	0.0137	0.0041	0.0096	0.0039	0.0011	0.0863
Renal cell carcinoma	0.0013	0.00017	0.0036	0.0010	0.0255	0.0190

Table III - P-values of the features

Subject Categories	P-values of the features derived					
	HOG	SURF	Contrast	Homogeneity	Correlation	Energy
Normal Subjects Renal cell carcinoma	0.0027	0.0018	0.00342	0.00103	0.0105	0.00061

The significant nature of the features is illustrated using the P value. This value describes mean significant difference among the features. These tables illustrate that the mean, standard deviation of the features are so significant. With these feature extracted, classification process occurs. Adaptive SVM in machine learning is used for the detection of carcinoma in the renal ultrasound images.

D. CLASSIFICATION

Features derived from the segmented images are subjected for the process of classification which involves training, testing and validation process. The features are significant from each other and therefore the training process is easy. In this process, the samples are trained and analyzed for the presence of carcinoma.

After training, validation is performed to define the efficiency of the classifier to illustrate the presence of carcinoma. In general 5-fold validation process is carried out using the performance parameters defined by the confusion matrix (See Table IV).

Table IV - Validation features of the classifier

	Valid1	Valid2	Valid3	Valid4	Valid5	Average
Accuracy	92.45	93.30	94.45	96.30	98.53	95.02±2.78
Precision	92.2	93.8	94.9	97.2	99	95.42±2.08

The cross validation process defines the training state of the classifier defined to be 95%. After validation, testing with sample images is done to describe the presence of carcinoma. Confusion matrix describes the true and false rates of the process of classification and defines the performance parameters of the classifier. With this matrix the classifier defines an accuracy of 96% in defining the renal cell carcinoma and normal conditions (See Table V).

Table V- Confusion matrix for Adaptive SVM

	Normal	Renal Carcinoma
Normal	96	4
Renal Carcinoma	6	94

In this algorithm defined, features extracted define the state whether carcinoma is present or not after the process of classification.

With the classification results, the renal carcinoma is detected and analyzed from the ultrasound renal images.

V.CONCLUSION

Cancer is becoming predominant among people throughout the world. There are different types of carcinoma formed in the renal system. Most commonly occurring carcinoma condition is renal cell carcinoma. Causes may be different but all cancer requires early diagnosis for treatment. Automatic algorithm for the detection and diagnosis of renal carcinoma is defined in this study. Renal images are derived from the database and undergo image processing techniques like filtering, region growing, feature extraction and classification. In this method, histogram based oriented gradient and Speeded up robust features are feature descriptors extracted for the detection of the renal cell carcinoma. These features possess a significant difference between the normal and abnormal conditions. With these features classification is performed with Adaptive SVM for detection of renal cell carcinoma. Thus the proposed algorithm can be implemented for different renal ultrasound images for early detection, diagnosis and treatment of disorders.

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